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Modeling and Optimization of Machining Parameters for Minimizing Surface Roughness and Tool Wear for EN100Cr6 Steel Dry Turning

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ABSTRACT

Sustainable manufacturing is a priority because along with the factors like productivity, time cycle and cost optimization in a process, the effect of machining on environment and the operator equally matters. In order to take it in a consideration, dry machining is promoted over the conventional machining procedures. Therefore modelling and optimization is required to figure out correct cutting condition for desirable machinability results. EN100Cr6 range of products like Plates/Sheets/Steel bars/Coil strip / Pipe & tubes.

During the study about the topic, EN-100Cr6 steel was turned under dry machining situations in order to optimize the way to enhance two factors called as surface roughness (Ra) and tool wear. As we all know that dumping the coolant & chip mixture is really been a quite tough procedure, that is the why conventional method of turning with a coolant is usually considered harmful for the environment. To find a solution to this problem, RSM was used for building a link between output & input parameters and finding out the optimize solution.

The optimum levels of the factors obtained for the cutting conditions are feed rate at 0.10 mm/rev, cutting speed at 80.0 m/min and depth of cut at 0.680 mm; and corresponding the values obtained for tool wear and surface roughness (Ra) are 0.03502580 mm & 3.380310µm. Model fitness and efficacy were judged by the confirmation tests.

The correlation coefficient (R2) of 0.9876 for tool wear and 0.9921 for surface roughness indicates a correlation between the predictions of models and results obtained after experiments. So, to minimize the number of experimental trails RSM model has been proved to be the excellent tool to find optimized results.

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KEYWORDS: *Surface roughness Ra, Dry turning, Optimization, Tool wear, EN-100Cr6 Steel*

INTRODUCTION

100Cr6 is a through hardening bearing steels intended for rolling contact and other high fatigue applications. In the hardened condition the high hardness, high strength and high cleanliness provides the steel with the right properties to withstand high cycle, high stress fatigue. 100Cr6 is mainly used for small and medium sized bearing components.

The hardenability approximately corresponds to a ring with max. 17 mm wall thickness. It is also regularly used for other machine components that require high tensile strength and high hardness

As observed, that during turning or in any other machining process the heat is generated at the tool-workspace point of contact which results in reducing tool life, improper machining and unsafe procedure. To get out of this coolant is used to at intermediate surface to absorb heat of chips and lubrication to avoid friction heat but it affects decomposition affects the environment [27, 32].

As per literature study it can be concluded that dry machining which are based upon multi-response optimization remains area which can have a space for

more research, so for the present study optimization of dry turning parameters and its effect on surface roughness and tool wear for EN100Cr6 was chosen. Machining under dry conditions were considered to be environment friendly process because of coolant absent [30, 36], as observed in other practices like assisted machining [29, 4] MQL [33, 34] green & Ultrasonic hybrid machining [15,34]. Taguchi & Grey relation based multi-objective optimization [24,7] many multi response models, response surface methodology based mathematical model, tool wear using RSM based models [9-11] are some of the researches conducted to swap the use of conventional machining method.

1. Materials and procedures

As mentioned in Table 1 that is clearly mentioning the asked 3 levels of chosen variables depends on previous data of various research works. When we were turning the EN100Cr6 steel, the effect of optimal cutting speed, feed, and depth of cut on surface finish & tool wear were observed. I have observed that there was certain effect of all above factors significantly over these 2 responses. RSM was used for study since it helps in forecasting the important association between the dependent & independent variables. With the help of the software, we are able to find the correlation for what we are looking for a while.

Table 1 Tool wear & Surface roughness (Ra) chart in turning of EN100 CR6

		Basic factors affecting cutting of tool		Variable factors of machining	
Exp No.	Factor 1 A: Speed (m/min)	Factor 2 B: Feed (mm/rev)	Factor3 C: Doc (mm)	Response 1 Roughness (μm)	Response 2 Tool wear (mm)
1	130	0.2	0.6	2.46	0.077
2	130	0.25	0.6	3.23	0.084
3	130	0.3	0.5	4.45	0.108
4	130	0.2	0.6	2.85	0.084
5	130	0.2	0.94	3.23	0.096
6	80	0.3	0.8	7.39	0.088
7	80	0.2	0.6	5.36	0.053
8	80	0.3	0.4	6.77	0.084
9	180	0.3	0.5	5.51	0.239
10	180	0.1	0.8	2.95	0.192
11	130	0.2	0.45	2.47	0.073
12	80	0.1	0.68	3.3801	0.035
13	130	0.37	0.6	7.53	0.188
14	130	0.2	0.6	5.02	0.122
15	180	0.2	0.6	2.3	0.176
16	180	0.1	0.4	1.95	0.157
17	130	0.2	0.55	5.35	0.126
18	180	0.3	0.8	6.51	0.312
19	130	0.2	0.6	7.21	0.165
20	80	0.1	0.8	3.83	0.047

2. Chemical composition of Work piece Material

EN-100CR6 steel chemical composition is described below with the weight percentage as given in Table 2. EN100Cr6 exhibits easy mechanical treatment, Good hardness, abrasion resistance to wear. This combination effects all properties of the steel.

Table 2 EN 100Cr6 Composition in weight percentage

ELEMENTS	Wt. %age
C	1.05
Mn	0.35
Si	0.23
S	0.028
P	0.01
Cr	1.45
Cu	0.28
Mo	0.04

2.1. RSM (Response Surface Methodology)

Here we have used the software which was used for the study to optimize multi-response named as Design expert DX7. To get the desired optimum values of factorial variable the Response surface methodology is used. The quadratic equation is given as $A = f(B1, B2, B3) + €$ Here, € is the error in response. The expected response is represented as -: $E(A) = f(B1, B2, B3) = \eta$ ………………….. (1) The surface value is given by $\eta = f(B1, B2, B3)$. Our focus is to optimize working conditions for the regression eqs which were derived as (eqs 2 & 3) on the other side Fig 1 represents the correlation plots for surface roughness and Tool wear whereas,

Regression eqs:-

$Ra = 2.235110 - (0.059320 \times Vc) + (7.659110 \times fr) + (1.056660 \times ap) - (0.00110 \times Vb \times fr) + (0.00850 \times Vb \times ap) + (1.7520 \times fr \times ap) - (0.0000381 \times Vb2) + (25.5101 \times fr^{2)} - (0.510 \times ap2)$…………………. (2)

$Vb = (0.1907720 - 0.001680 \times Vc) - (1.115620 \times fr) - (0.08915560 \times ap) + (0.0037210 \times Vc \times ap) + (0.33310 \times fr \times ap) + (0.000069880 \times Vc^2) + (1.760 \times fr^2) - (4.238E^{-16} \times ap2)$…………………...(3).

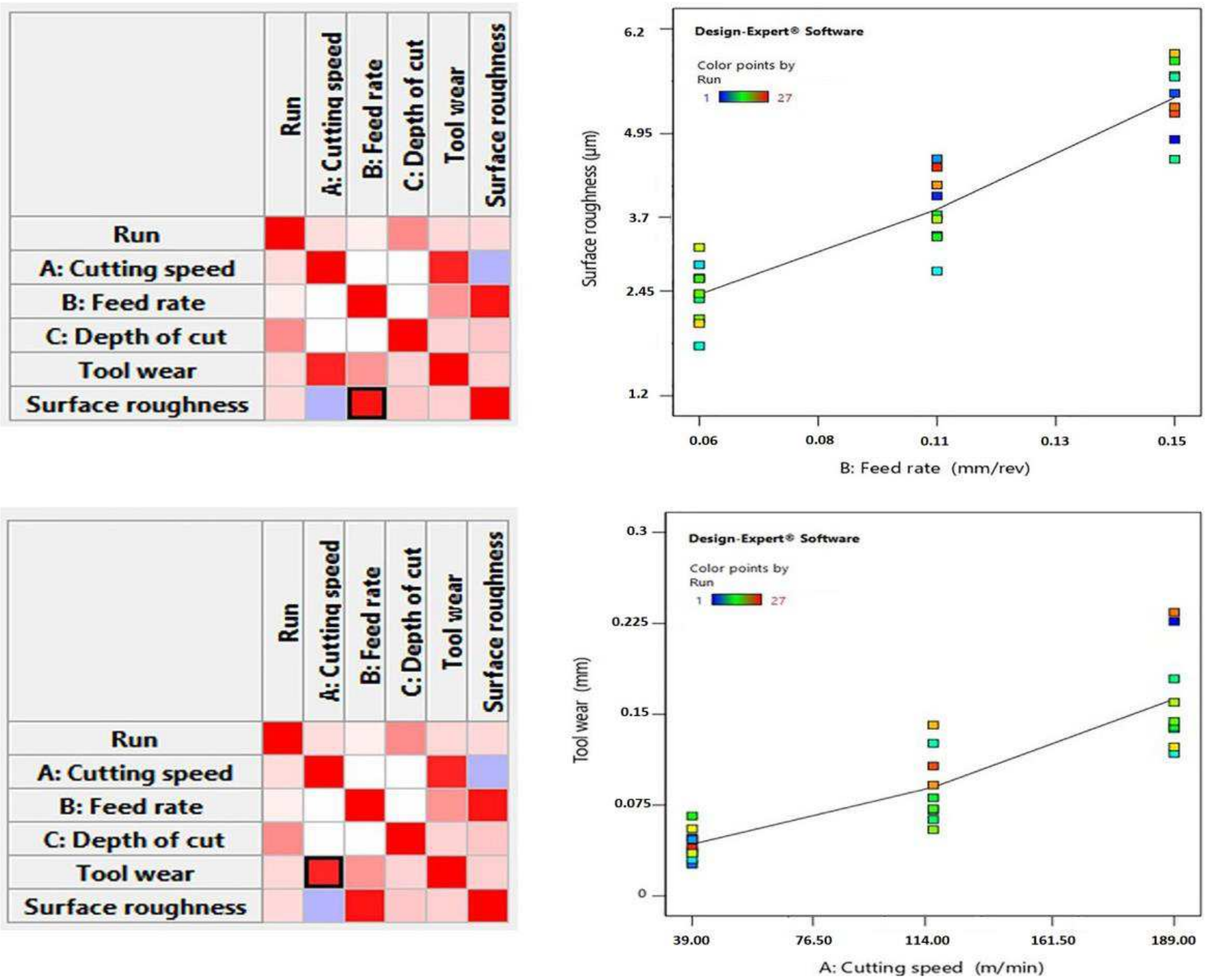

Fig 1 Tool wear and surface roughness correlation grid plots.

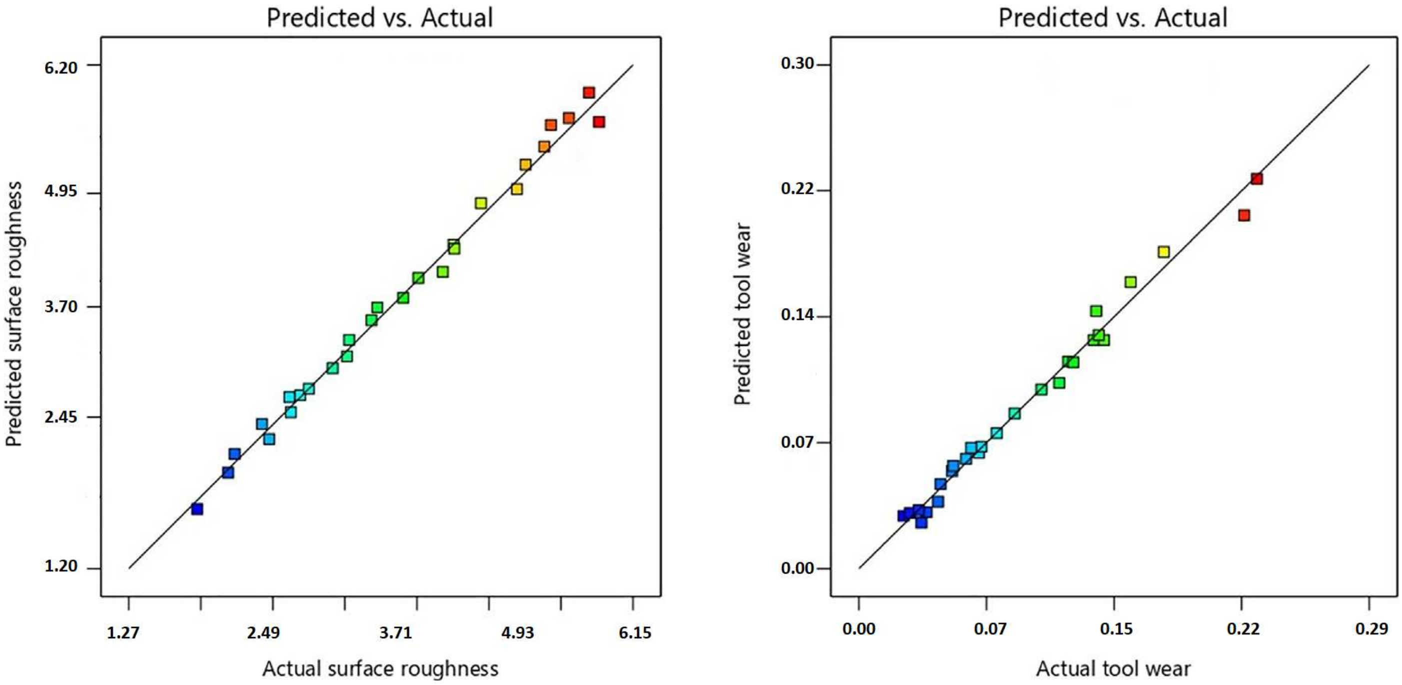

Fig 2 Tool wear & Surface roughness graphs for actual v/s predicted values

2.2. Test of Statistical Significance

Both tests mentioned below were used for testing the statistical validation:-

1. Test for the regression model significance (this will help in testing for validation)
2. Predicted model adequacy (This model is quite useful in testifying the results)

1. Test for regression model significance

In Table 3, surface roughness (Ra) has been tested by ANOVA and for tool wear in Table 4. As we get the value of 0.0500 > P, As here we are saying that we use ANOVA for calculating the F-value. A correlation has been established that the Error would be said minimal if an only if the F value is large.

2. Predicted model adequacy

In Fig 3, the plots in between the responses that are predicted and normal probability of residuals. In this we are showing below graphs that gives clear scenario about the factors effects and their comparison. Here we have confirm that if there is a straight line pattern while making the plot of normal probability of residuals then it is permissible. Similarly residual vs predicted response will make a little different pattern and within red lines.

Table 3 ANOVA table (Surface Roughness)

Source	Sum of Squares	Df	Mean Square	F Value	P- value Prob> F	%age contribution
Model	41.79	9	4.64	1.86	0.1746	92.1
A-cutting speed	5.83	1	5.83	2.33	0.1580	6.898
B-feed	18.84	1	18.84	7.53	0.0207	90.21
C-depth of cut	2.20	1	2.20	0.88	0.3706	2.88
AB	0.18	1	0.18	0.072	0.7939	0.015
AC	0.30	1	0.30	0.12	0.7350	0.111
BC	0.21	1	0.21	0.084	0.7776	0.014
A2	1.47	1	1.47	0.59	0.4609	0.069
B2	1.04	1	1.04	0.42	0.5327	0.557
C2	1.34	1	1.34	0.53	0.4814	0.0003
Residual	25.02	10	2.50			0.749
Cor Total	66.81	19				100

*represents that value is significant

In the above table which also called ANOVA table giving us the significant values and comparison and effect of variables. In above table\, factor A, B & C in a quadratic equation it is shown that F value is highest for the Feed and also feed is showing the maximum contribution as 90.21 % which clearly states that feed has most effective role in surface roughness.

Table 4 The ANOVA table (Tool Wear)

Source	Sum of Squares	Df	Mean Square	F Value	P- value Prob> F	%age contribution
Model	0.083	9	9.265	9.10	0.0013	93.24
A-cutting speed	0.053	1	0.053	51.98	< 0.0001	75.24
B-feed	6.689	1	6.689	6.57	0.0263	14.11
C-depth of cut	1.859	1	1.859	1.82	0.2320	2.21
AB	8.007	1	8.007	0.79	0.9512	3.10
AC	1.553	1	1.553	1.52	0.4759	0.235
BC	5.807	1	5.807	0.57	0.7233	0.446
A2	3.493	1	3.493	3.43	0.2363	1.854
B2	1.405	1	1.405	1.38	0.3359	0.007
C2	3.153	1	3.153	0.31	0.5683	0.000
Residual	0.010	10	1.019		0.0013	1.415
Cor Total	0.94	19				100

*represents that value is significant

In the above table which also called ANOVA table giving us the significant values and comparison and effect of variables. In above table\, factor A, B & C in a quadratic equation it is shown that F value is highest for the Feed and also feed is showing the maximum contribution as 75.24 % which clearly states that feed has most effective role in surface roughness.

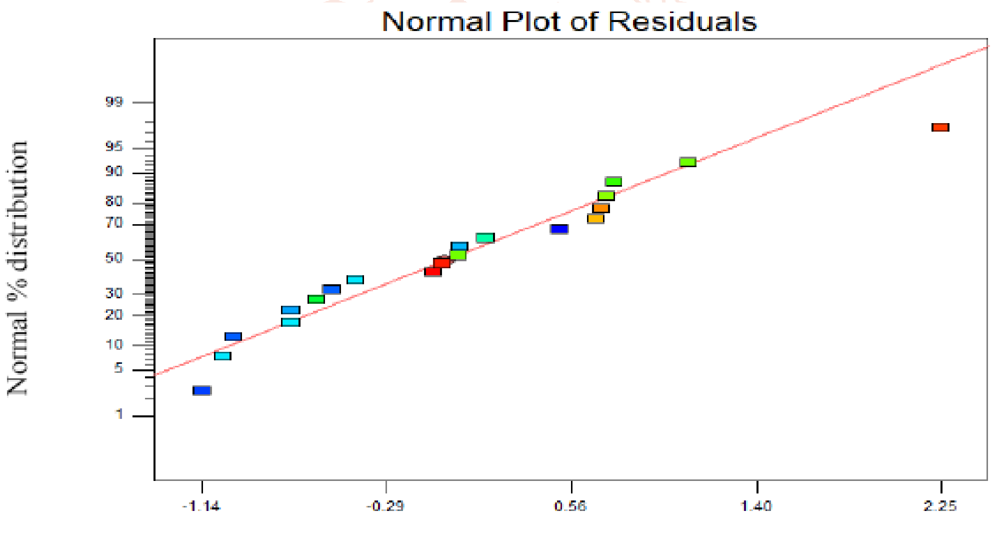

Fig 3 (a) Residuals plots for Surface roughness

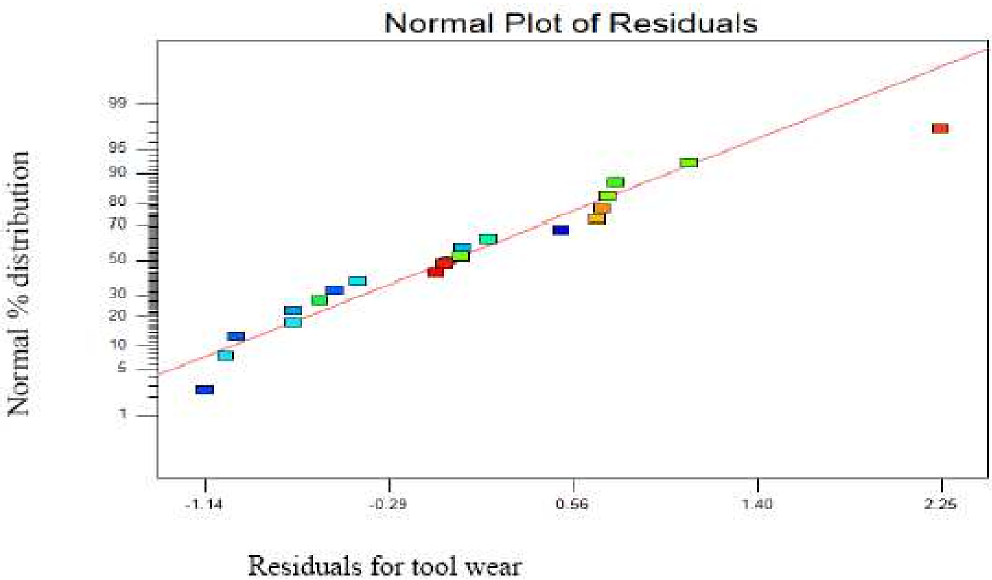

Fig 3 (b) Residuals plots for tool wear

The accuracy of the model can be clearly visible in table Fig 3 where normal plots of probability shown the exact straight line pattern with the plots of surface roughness & tool wear . The plot residual vs expected response looks like structure less, we can also say by going through chart that it is not following a particular pattern and laying between given red lines. We can say after going through above that model forecasting is correct and acceptable.

3. Results and Discussion

We know the role and effect of the surface roughness and irregularities on object when it interact with the environment. It is clearly visible here from the figure that surface roughness (Ra) varies directly proportional with the feed rate, similar results were visible from ANOVA table (Table.3). Below given 3D plots are formed using the RSM methodology in which a connection or comparison has been established between operating and output parameters. If surface roughness is high the irregularities will result in development of cracks at surface. As seen in Figure 5 it can be concluded that Tool wear varies directly proportional with speed of cut as tool edges faces the pressure consecutively (1 , 3). Same stated for ANOVA table (Table 4). In both the cases depth of cut has negligible effect.

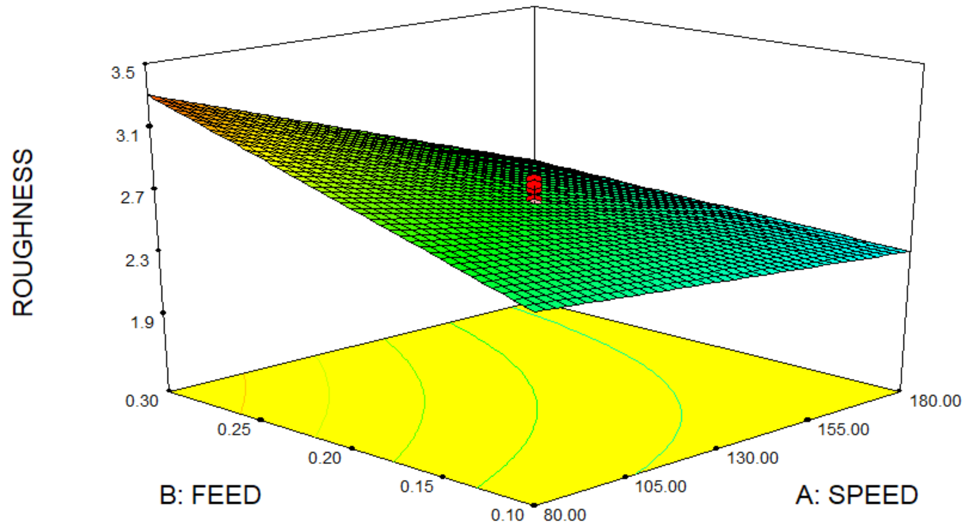

Fig 4 THREE DIMENSION SURFACE GRAPH (Surface Roughness)

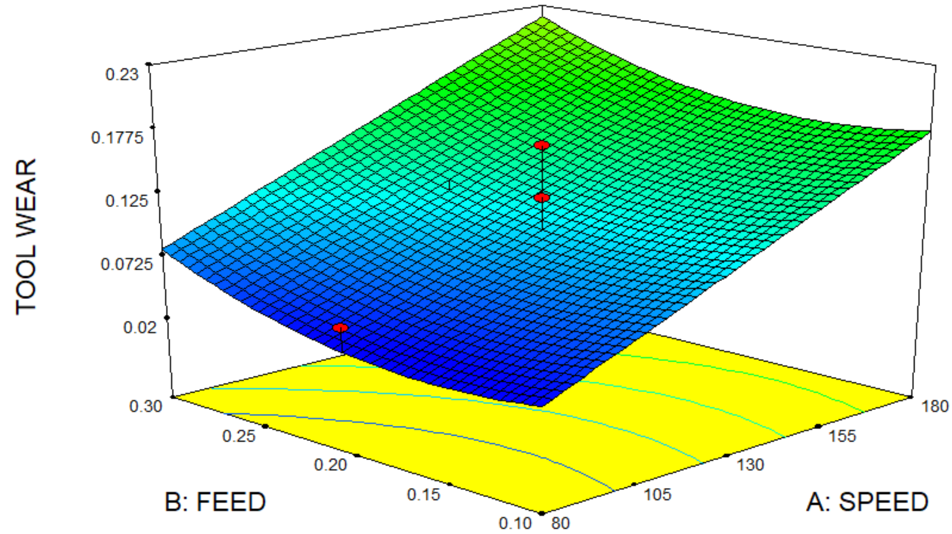

Fig 5 THREE DIMENSION SURFACE GRAPH (Tool Wear)

Table 5 Permissible limits chart for optimized parameters

Name	Target	Bottom limit	Top limit	Lower weight	Upper weight	Importance
Cutting speed	in range	80	180	01	01	03
Feed rate	in range	0.10	0.30	01	01	03
Depth of cut	in range	0.40	0.80	01	01	03
Surface roughness	Minimal value	1.950	7.530	01	01	03
Tool - wear	Minimal value	0.035000	0.31200	01	01	03

Here we can see in above table the correlation between output and operating parameters. We have formed a certain range for the values like setting a limit for all with their effect on output parameters (Tool wear and surface roughness). Our target is to keep both the values as low as possible to increase tool life and avoid conventional machining process.

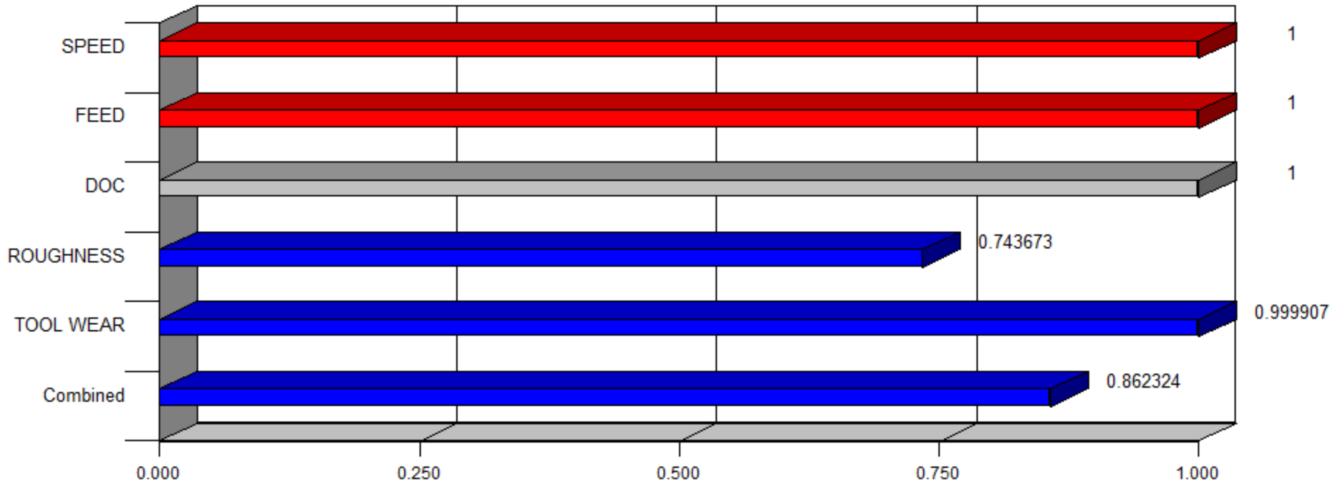

Fig 6. Desirability bar graph

Above graph shows clearly about the desirability, it provides the best possible value for each parameters. In above desirability graph, we can see that output parameters like surface roughness (Ra) & Tool wear combined one at the last one bar. Operating parameters like Depth of cut, Speed & feed and the combined desirability of 0.862324 is shown in the last bar.

Table 6 Optimized machining parameters

S.no	Cutting speed	Feed	Depth of cut	Surface finish	Tool wear	Desirability	Remarks
1	80	0.1	0.68	3.3801	0.03500258	0.862	Selected

From above data, we have concluded that optimized values are depth of cut is 0.680 mm, feed as 0.100 milli-meter/rev & cutting speed at 80.00 meter/minute respectively. Optimized values found for all parameters as shown above. Optimum machining parameters can be achieved by keeping the values minimum.

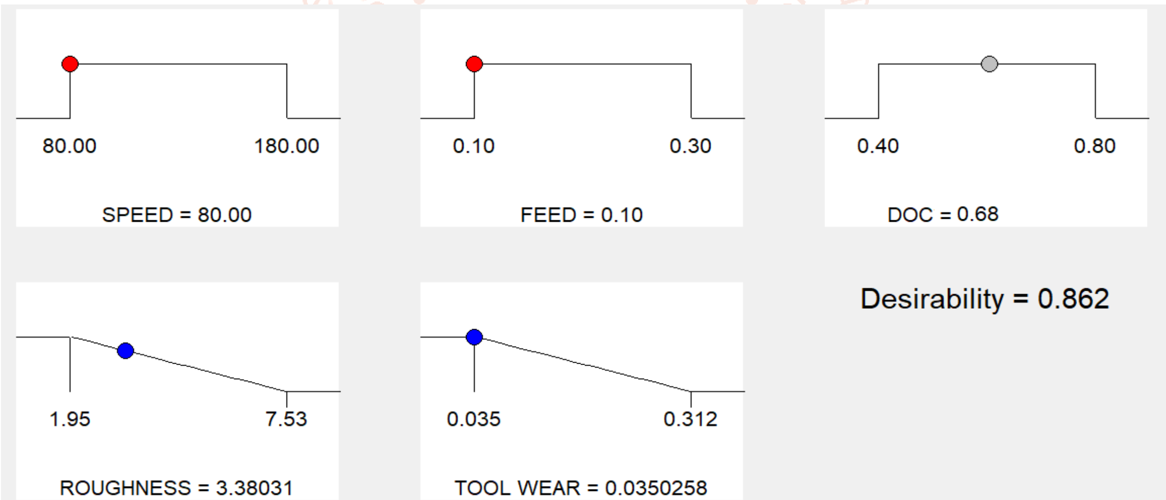

Fig 7 Desirability Ramp function graph

As we can see in Fig 7, ramp graphs showing optimized values of all input & output parameters along with the desirability which will help to get multi objective optimization. The values obtained from the desirability ramp graph were Wear of the tool as 0.03502580 and Roughness of the surface as 3.380310. Ramp graphs are always considered as the most comprehend ones.

Confirmation Test

Table 7 Validations results

Responses	Predicted	Experimental	Error
Surface roughness	1.89806	1.9976	4.98%
Tool Wear	0.0193025	0.0201	3.96 %

4. Conclusions

As mentioned in the beginning about the motive behind this research to find out optimized and modelling of the values of all three input parameters to minimize wear of the tool & roughness of the surface: -

- As mentioned above, we can conclude that speed of cutting tool has the major effect on tool wear followed by remaining 2 parameters. Similarly Feed affects the surface roughness most followed by rest 2 parameters.
- Optimized values for the specified parameters were like feed as 0.100 mm/rev, cutting speed as 80.00 m/min and 0.6800 mm as the depth of cut. The roughness of surface were obtained as 3.380310 mm. and the related Tool wear was 0.035025800 µm.
- Combined desirability of 86.4 percent was obtained in the study.
- As per the results, it is concluded that calculated errors were within the acceptable ranges.

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